Rainfall Anomaly Analysis and Seasonal Climate Projection in Palembang City Using CHIRPS Data and Z-Score Method

Shofwan Mahsyurdin
Master of Computer Science, Universitas Sriwijaya, South Sumatra, Indonesia

Ermatita
Master of Computer Science, Universitas Sriwijaya, South Sumatra, Indonesia

Abstract: Using CHIRPS daily rainfall data (1981–2024) which is the standard climatological period according to the World Meteorological Organization (WMO) which is at least 30 years, rainfall anomalies during the dry season (May–October) are analyzed using the Z-score statistical approach. The 2025 prediction scenario integrates moderate El Niño (SST +1.0) and negative IOD (–0.5) as correction factors for the climatological average. Anomalous rainfall values will be converted into z-score values if Z>0 then the value is above the average (wet/hot) and vice versa if Z<0 the value is below the average (dry/cold). The results of the study indicate a significant potential for negative anomalies (Z-score < 0) in most areas of Palembang, indicating a decrease in rainfall below normal levels, with the peak of the dry season projected in August–September 2025. For the rainfall anomaly value, it has been converted into a z-score value that has been explained using the formula so that the significant climate trend in 2024 is 0.34 according to the Standardized Rainfall Index (SPI) in the normal or mild condition category. Finally, the rainfall prediction graph for 2025 shows the final results of the analysis process, namely the highest rainfall of 369.173 mm in April and the lowest rainfall of 60.12 mm in August.

Keywords: Google Earth Engine, Z-score, ENSO, IOD, Rain, drought.

Correspondents Author:
Shofwan Mahsyurdin, Master of Computer Science, Universitas Sriwijaya, South Sumatra, Indonesia
Email: 09012622428004@student.unsri.ac.id

Received December 4 2025; Revised January 19, 2026; Accepted February 6, 2026; Published February 14, 2026.

Introduction

Differences in interpretation can cause confusion for users and ultimately reduce the quality of the information received. The presentation of weather information needs to be designed in such a way that it can be optimally utilized by the public. The implications of this study extend far beyond the basin of interest. It highlights the broader relevance of integrating machine learning, remote sensing, and biophysical data to understand urban dynamics (Durowoju, 2025). There are varying perceptions regarding user databases related to observed weather objects. Data collection methods in the digital era have shifted conventional processes, thus requiring emphasis on systems or technology to ensure the resulting data remains balanced, in addition to that, the regional boundaries are focused on the city of Palembang which must align perceptions with the reach of the IOD (Indian Ocean) and ENSO (Pacific Ocean) covering a wide area. The relationship between Palembang's perception of the Indian Ocean Dipole (IOD) and El Niño Southern Oscillation (ENSO) is crucial because the city is highly sensitive to both phenomena. Its low-lying conditions make it vulnerable to rainy seasons and flooding, and its swampy landscape often leads to drastic changes between periods of extreme drought and forest fires. There are many ways to overcome climate prediction with Zscore, including CHIRPS data collection, data normalization with Zscore, and location mapping analysis.

Harnessing the power of geospatial data and satellite imagery to collect actionable information in real time can dramatically change the status quo and create a new paradigm for combating climate risks (Levin, 2023). There are several major limitations of research on climate anomalies at the urban scale such as Uncertainty of climate models, Limited spatial resolution, long historical data (> 30 years) and Limitations in Prediction. It aids in the development of sustainable water management strategies and plans, supporting the preservation and effective use of water resources (Garajeh, 2024). Collective data processing can be assisted by structured, systematic, and well-designed software. In climatology studies, the Z-score serves as a tool for detecting significant deviations from historical averages, known as anomalies. The magnitude of this score whether positive or negative, is a crucial indicator of extreme weather in projecting natural phenomena such as droughts.

The process of retrieving information and collecting data can be assisted by using software supported by statistical calculations, mathematics, or Artificial Intelligence (AI) technology. In addition, this study opens opportunities for further studies on the factors that influence the trends through using sub-daily and daily satellite data for a relatively longer period i.e., >30 years (Gwatida, 2023). Starting a program cannot be done drastically because it requires keeping up with constantly changing and updated data. However, it is difficult toensure the accuracy of the tracking for the strong convectiveweather process with rapid change of echo image because it is only simple to calculate the correlation coefficient (Sun, 2021). They observed considerable discrepancies between the diurnal cycle of observed and bias-corrected precipitation and much less variability in temperature, but they still recommend bias-correcting the diurnal cycle in case of climate change impact investigation on sub-daily temporal resolution (Dhawan, 2024). This study investigates the utility of employing Global Satellite Precipitation (GSP) in conjunction with ground-based precipitation data. Monthly studies of the research area were performed using fourteen various GSP models, including CHIRPS, CFS, CPC CMORPH, and others (Habibie, 2024).

This baseline can serve as a reference as a crucial variable in determining samples for processing climate prediction data, which can change significantly. Regional variability of rainfall extremes was analysed using the coupled Empirical Orthogonal Function method and K-means clustering algorithm (Alzian, 2025). Understanding rainfall patterns is crucial for guiding strategic planning and enhancing resilience across relevant sectors or agencies to mitigate climate variability and natural disasters (Andriyana, 2024). Based on the formulation of the problem in this study, several attributes will be used for the analysis process using the anomaly Zscore method. Climate change has further amplified the frequency and severity of extreme weather events, increased the volatility of rainfall pattern and complicated traditional forecasting efforts (Amir, 2025). The main functions of rainfall modeling in this study are identifying relationships between variables, simplifying atmospheric complexity, quantifying weather impacts (weighting), and estimating future monitoring. Significant contributions to this study include improving accuracy through integrated predictions, providing a basis for disaster mitigation, and providing regional planning.

Research Method

Z-score based climatological anomaly analysis

The Z-Score is another important statistical tool commonly used in multivariate analysis. This can be proven in the formula in the multivariate analysis summary which shows that the Z-score in multivariate regression analysis is used to determine how far a variable's value is from its mean, in standard deviation units. With the working concept of Transformation to Z-Score, each data value for each variable (both dependent and independent) is transformed into a Z-score. The Z-score helps identify unusual or extreme climate events, such as severe heat waves or periods of significant drought. A large absolute value of the Z-score indicates an anomaly. Therefore, the general formula for the Z Score is seen in equation (1).

$$Z = (X - \mu) / \sigma \tag{1}$$

where X = value of the variable for which you want to calculate the Z-score, μ = mean of the variable, σ = standard deviation of the variable, If the Mathematical Variable is described then written in formal scientific climatology notation, The Z-score algorithm follows equation (2):

$$Z= (x_{2025} - \bar{x}_{climatology})/ \sigma_{climatology} \quad (2)$$

Where X_{2025} = Accumulate predicted rainfall, $\overline{X}_{climatology}$ = Climatological average (usually 30-year period) and $\sigma_{climatology}$ = Standard deviation indicating the spread of historical data.

Google Earth Engine Application in Climate Prediction

In the Google Earth Engine (GEE) ecosystem, boundaries, often referred to as Regions of Interest (ROI), play a vital role. Therefore, boundaries play a key role in CHIRPS data processing, such as spatial filters, spatial reduction, masking or clipping, and standardization of analysis units. It's important to emphasize that conducting research using open-source algorithms requires a robust database for the application's system to run smoothly. Therefore, researchers have mapped the study area to ensure a precise assessment. var palembang = ee. FeatureCollection ('projects/your name/assets/Palembang'); Retrieving the Palembang City boundary shapefile from the user's assets, including data from the downloaded shapefile, will produce a Palembang City boundary map that can be viewed visually.

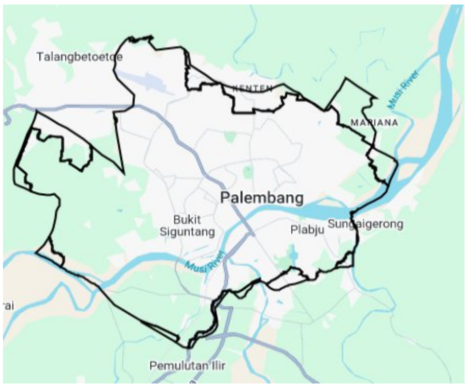

Figure 1 Boundary Maps of Palembang City Area

The image above demonstrates that data from CHIRPS (Climate Hazards Group InfraRed Precipitation with Station) can be used to analyze rainfall and climate conditions in Palembang. The function of the reduceRegions () algorithm code uses boundaries to determine which pixels should be calculated for the average, median or total. Palembang's boundary data can be accessed in shapefile (SHP), KML, and GeoJSON formats through various sources. In contrast to other GPPs, CHIRPS is not always the best product, but it is considerably well in capturing monthly precipitation and is suitable for assessing drought (Du, 2023).

Work Concept

Earth Engine combines a multi-petabyte catalog of analysis-ready satellite imagery and remote sensing data with Google-scale computing, enabling you to perform planet-scale analyses—all from within your browser. Using Earth Engine, you can track surface temperature, changes in vegetation cover, and even biodiversity. Earth Engine is highly effective and capable of monitoring all aspects of the environment and zoning. In remote sensing observations, rainfall is calculated using the knowledge of electromagnetic waves emitted by clouds and captured by satellites/radar (Simanjuntak, 2024). Earth Engine includes a database of satellite imagery and remote sensing data. Analysis results can be visualized directly on the map through the Code Editor environment or exported as files (such as GeoTIFF) for use in other software or as an intermediate matrix.

Dataset

CHIRPS Data Pre-Processing Workflow

The dataset structure used in this study includes Feature Collection, Image Collection, Image, and Feature Collection. The initial step in this study will be to retrieve the CHIRPS datasheet on daily rainfall for the period 1981-2024 in the Palembang area. In the Time-Space Matrix Structure format, each row represents time and each column represents a specific location (Pixel/Grid). From the data that has been downloaded from CHIRPS, it can be proven again through Table 1 regarding the average rainfall data matrix for the period 1981-2024) which is sorted periodically. Structured rainfall matrices are typically arranged in a 2D (Row x Column) format to facilitate statistical computation and machine learning algorithms. To change the time scale, use the Temporal Aggregation Technique, which is the process of summarizing high-resolution (daily) data into lower-resolution (monthly, seasonal, or annual) data. For rainfall, the method used is Summation, not average. Therefore, a formula must be created to make the unit adjustment clearer.

Monthly aggregation is the summing of all mm/day values within a month.

$$\mathrm{P}_{\text{month}} = \sum_{i=1}^{n} P_{\text{day\_i}} \tag{3}$$

Where n = total days in a month and P = Precipitation, Annual aggregation is often performed over a full year (mm/years), This unit will be used because the calculation scale is one climate period. Baseline (Climatology) is established to calculate the average monthly rainfall over a 30-year reference period. Meanwhile, to analyze anomalies, there are calculations, including: Positive Anomaly: Above-average rainfall (potential for flooding/La Niña), Negative Anomaly: Below-average rainfall (potential for drought/El Niño).

Table 1 CHIRPS data (average rainfall data)

CHIRPS data (average rainfall data)				
Year	**precipitation (mm/ years)**		**Year**	**precipitation (mm/ years)**
1981	1,164.75		2003	857.839
1982	583.129		2004	781.156
1983	915.972		2005	1,100.945
1984	1,214.628		2006	755.863
1985	1,139.051		2007	956.493
1986	1,022.95		2008	766.183
1987	622.661		2009	726.09
1988	870.789		2010	1,485.787
1989	883.757		2011	757.238
1990	756.44		2012	731.309
1991	434.388		2013	1,130.086
1992	981.154		2014	707.198
1993	822.401		2015	332.35
1994	372.873		2016	1,118.287
1995	973.651		2017	1,087.561
1996	1,214.419		2018	930.957
1997	352.645		2019	466.323
1998	1,327.05		2020	1,287.294
1999	829.102		2021	1,313.661
2000	1,142.534		2022	1,466.807
2001	1,164.495		2023	668.995
2002	526.327		2024	966.026

The function can be clarified in Table 2 which explains climatology and geographic climate, based on several elements of climate dynamics which are influenced by other factors, so that the perspective aspect is more complex, the function of climatology and geographic climate is described below.

Table 2 Geographical Functions of Meteorology and Climate

Climatology	Geographic Climate
Calculating the average (climatology) and Z-score anomalies.	Provides global daily rainfall data with high spatial resolution (~5 km).
Mitigation planning and management of water resources, especially in areas prone to flooding and drought.	Making rainfall projections for 2025 (with ENSO/IOD modifications).
Looking at long-term trends and climate fluctuations in Palembang.	Calculate the accumulated rainfall and dry season each year.

The integration of climatological functions and geographic approaches, as shown in Table 2, is a crucial foundation for understanding hydrometeorological dynamics, particularly in specific regions such as Palembang. Technically, calculating average values and Z-scores (anomalies) from climatological data provides a deep understanding of climate deviations. Data will be more meaningful when combined with high spatial resolution geographic parameters up to ~5 km. By utilizing precise global daily rainfall data, researchers can map rainfall and dry season duration in detail. This interrelationship allows for the modification of external variables such as ENSO (El Niño-Southern Oscillation) and IOD (Indian Ocean Dipole) into the 2025 rainfall projection, resulting in more accurate estimates of long-term climate projections. Correlation analysis and four machine learning algorithms (random forest, decision tree regression, linear regression, and support vector regression) were used to analyze ozone and meteorological dataset in the study area. The analysis was carried out during the southwest monsoon due to the rise of ozone in the dry season (Balogun, 2022).

Based on the current conditions and existing literature, the integrated use of complex atmospheric variables and multivariate approaches in rainfall modeling, so far, remains significantly underexplored. The primary relevance of combining these two functions to research lies in the ability to transform raw data into applicable policy instruments. Long-term trend analysis in Palembang serves not only as a historical record but also as a baseline for mitigation planning and air resource management. Therefore, presenting this function table in research is crucial (a fundamental aspect); the table serves as a methodological framework explaining how atmospheric data is converted into measurable geographic information units, thus providing strong scientific justification for future climate adaptation strategies. Meteorological data of different synoptic stations, including different climates, are collected and analyzed (Sharafi, 2021).

Programming Process Flow

The research process for processing climate data using Google Earth Engine (GEE) begins with determining the research objectives, such as analyzing rainfall or temperature. The results of data processing are then analyzed to answer research questions, and visualizations of the analysis results are created to facilitate understanding. An algorithm trained on historical rainfall measurements would then process the data. Using remote monitoring instrument input features, the machine-learning model can predict precipitation. The first steps to take are to explore and search for the identification of a region's database through satellite imagery for the main purpose of this research, such as analyzing rainfall, temperature, or other climate phenomena. Collect climate data from various sources, such as satellite data (e.g., MODIS, Landsat, Sentinel), climatological data (e.g., CHIRPS, TRMM), and weather data (e.g., BMKG weather stations or other parties).

To provide a comprehensive overview of the climate data processing mechanism within the Google Earth Engine ecosystem, a systematic flow from image extraction to prediction generation should be structured in a flowchart. Researchers prioritize climatological data, namely taking samples from "CHIRPS Daily" data. Focus on the data to be processed regarding rainfall patterns, analyze graphs, interpret the analysis results, and draw conclusions relevant to the objectives. Therefore, there needs to be collaboration between Pre-Processing and Processing Modeling in the form of a workflow identification concept that can be proven in Figure 3 with its algorithmic process flow.

Figure 2 Identifying the Workflow of Chirps Daily

Based on Figure 2 would be even more comprehensive if the researcher explained in detail with a visual representation of an interconnected process in a flowchart (Figure 3). The purpose of this is to help explain the workflow clearly, concisely, and easily, especially in research development that identifies errors (failures) or weaknesses in the system, improve efficiency, and provide clear guidelines for system development.

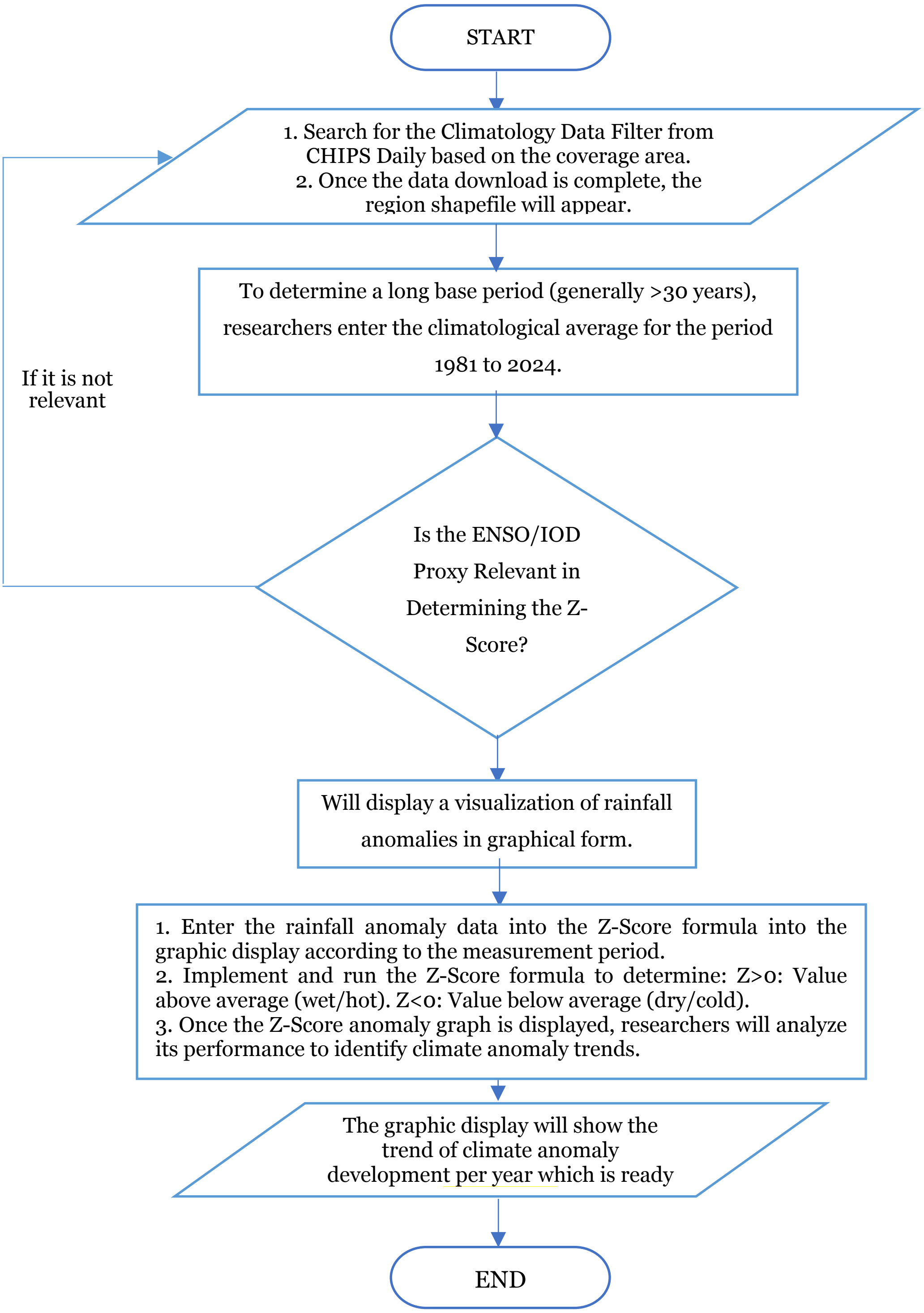

Figure 3 Flowchart of Programming Flow in GEE

The research workflow (flowchart) above, which relates to climate prediction using Google Earth Engine (GEE), begins with the identification of the problem and research objectives, namely, to understand how changes in temperature and rainfall affect environmental conditions in a region and to predict future climate trends. The data obtained then goes through a pre-processing stage, such as proxies from mapping regions in the context of the global El Nino-Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD), which are factors relevant to climate phenomena. Rainfall statistics were derived using the CHIRPS gridded precipitation data package (Rahayu, 2022).

From the results of this analysis, researchers build a climate prediction model using the Linear Regression machine learning algorithm available in GEE. The results of the model are then visualized in the form of interactive maps and graphs on the GEE platform to display the spatial distribution of priority rainfall and areas that are potentially experiencing extreme changes. The results will also be visually displayed in the form of a “monthly rainfall” graph, which is the output of Post-Processing and Finishing Processing from a study.

Result and Discussion

Problem Solving Analysis

Critical interpretation of the modeling results shows the rainfall anomaly value for the period 1981 to 2024. This needs to be converted to a z-score value so that we can determine rainfall trends and patterns in the climate. The sharp fluctuation in rainfall between the peak of the rainy season in April and the lowest point in August indicates the strong influence of large-scale climate phenomena. Specifically, this condition needs to be correlated with the dynamics of the El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD); where high Z-Score values often signal positive (wet) anomalies due to La Niña or negative IOD conditions that increase evaporation in the Indian Ocean. Without this global integration variable in post-processing, the model risks bias in distinguishing between normal seasonal cycles and extreme climate anomalies that could trigger hydrometeorological disasters in Palembang City. Given that the researchers had conducted a series of international literature reviews, the final data cleaning and validation process was crucial. This was done to ensure the accuracy of the predictions and their consistency against the influence of unforeseen external variables.

Algorithm Stages in Rainfall Data Filtering and Spatial Visualization.

The implementation of this algorithm begins with estimating accumulated rainfall for a specific period using the time-slice method on the CHIRPS dataset. In the 2025 scenario (using 2024 proxy data), the algorithm performs temporal aggregation by summing all precipitation pixel values within a predetermined month range (in this case, the dry season months). This process then involves a multiplication operator with a factor variable, which serves as a physical adjustment parameter or bias correction to model the rainfall projection for the coming year more representatively.

As an initial step in starting the program after obtaining data from CHIRPS, it will display a visual graph shown in Figure 4, which is the program algorithm for the annual rainfall graph of Palembang City for the period 1981–2024. Next, to understand the statistical significance of these accumulated values, a normalized anomaly (Z-score) calculation is performed. Scientifically, this process aims to measure the extent to which the 2025 rainfall projection deviates from the climatological average (climMean). By dividing the difference between the predicted values and the mean by the standard deviation (climStd), the algorithm produces a unitless score indicating the level of extreme variability. The final result, a z-score map, allows the identification of areas that will statistically experience significantly drier (strong negative values) or significantly wetter (strong positive values) conditions compared to their historical normal, which is crucial for mitigating hydrometeorological disaster risks.

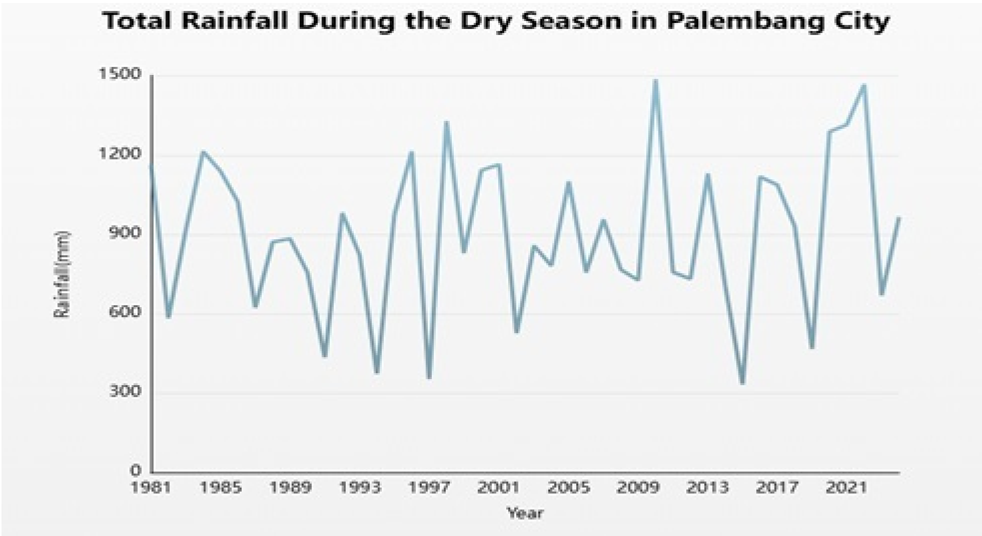

Figure 4 Graph of Total Rainfall During the Dry Season in Palembang City (1981-2024)

This line graph or Figure 4 displays historical data on total rainfall recorded during the dry season (May-October) in Palembang City from 1981 to 2024. Various assumptions made in analyzing this data reveal the following important points:

1. Rainfall Fluctuations: The data shows significant fluctuations from year to year, with no consistent long-term upward or downward trend. This indicates high climate variability in the region during the dry season.
2. Rainfall Peaks: There have been several years with very high rainfall during the dry season, far exceeding the average, such as 1998, 2010, and 2023, which showed the highest peaks, reaching around 1,400 mm to 1,500 mm.
3. Lowest Rainfall: Several periods recorded relatively low dry season rainfall, although rarely approaching zero, such as in 1994, 1997, and 2015. The lowest rainfall was close to 300-400 mm.

Anomaly Normalization

Previously obtained data regarding rainfall is collected and then converted to normalize the anomaly value. We must run the z-score formula to get a visual of the z-score time series graph data. The calculation steps can be explained as follows:

1. Annual Rainfall Aggregation: In this stage, daily rainfall data are summed to obtain the total annual rainfall. Climatological data measurements from 1981 to 2024 are used to obtain a stable average for the months within a specific timeframe.
2. Mean Value Extraction: Data quality control is used to extract the average annual rainfall value for the Palembang region. This process produces a representative rainfall value for the region for each observation year.
3. Z-Score Conversion and Calculation: The total annual rainfall value obtained is then calculated using a standard formula to determine its Z-score anomaly. The rainfall value for a given year is subtracted from the long-term climatological average, and the result is divided by the long-term climatological standard deviation. This procedure produces a Z-score that describes the position of annual rainfall relative to its historical normal.

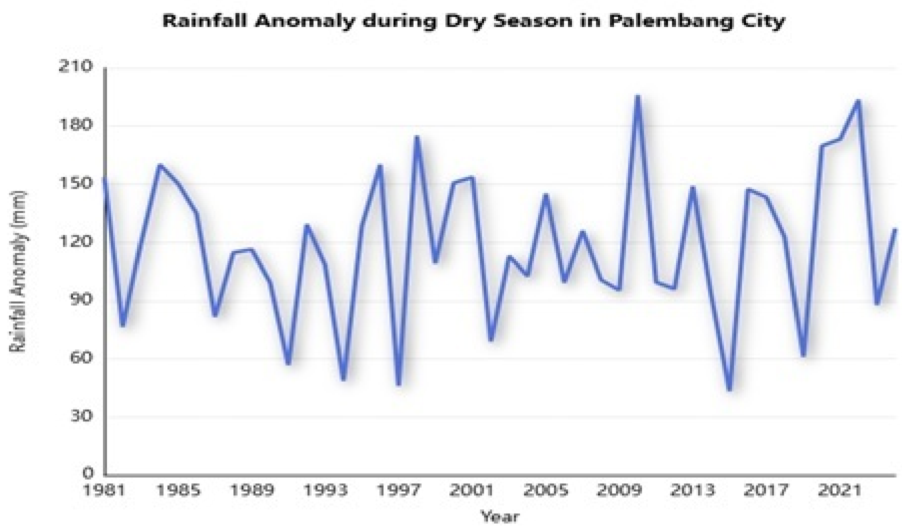

Figure 5 Annual Rainfall Anomaly Graphic Display

Based on the Z-score anomaly graph in Figure 5 for the dry season in Palembang City from 1981 to 2024, it can be seen that rainfall variability has changed significantly from year to year. The Z-score itself is a statistical measure that describes how far a value—in this case rainfall—deviates from its historical average. A positive Z-score value indicates that rainfall is above average (indicating a wet dry season), while a negative value indicates that rainfall is below average (indicating a dry dry season or signs of drought). To implement formula (1) it will be explained in table 3 to determine the anomaly zscore value.

Table 3 Implementation of the Z-Score anomaly value formula

Year	Rainfall Anomaly mm/year	Standard Deviastion (σ)	Z-Score Value
1981	153,53	25	1,39
1982	76,54	25	-1,69
1983	120,60	25	0,07
1984	160,13	25	1,65
1985	150,13	25	1,25
1986	134,76	25	0,64
1987	81,77	25	-1,48
1988	114,62	25	-0,17
1989	116,34	25	-0,10
1990	99,48	25	-0,77
1991	56,85	25	-2,48
1992	129,23	25	0,42
1993	108,21	25	-0,42
1994	48,71	25	-2,80
1995	128,24	25	0,38
1996	160,11	25	1,65
1997	46,03	25	-2,91
1998	175,02	25	2,25
1999	109,10	25	-0,39
2000	150,59	25	1,27
2001	153,50	25	1,39
2002	69,02	25	-1,99
2003	112,91	25	-0,24
2004	102,75	25	-0,64
2005	145,09	25	1,05
2006	99,41	25	-0,78
2007	125,96	25	0,29
2008	100,77	25	-0,72
2009	95,47	25	-0,93
2010	196,03	25	3,09
2011	99,59	25	-0,77
2012	96,16	25	-0,91
2013	148,94	25	1,21
2014	92,96	25	-1,03
2015	43,35	25	-3,02
2016	147,38	25	1,14
2017	143,31	25	0,98
2018	122,58	25	0,15
2019	61,08	25	-2,31
2020	169,75	25	2,04
2021	173,24	25	2,18

2022	193,52	25	2,99
2023	87,91	25	-1,24
2024	127,23	25	0,34

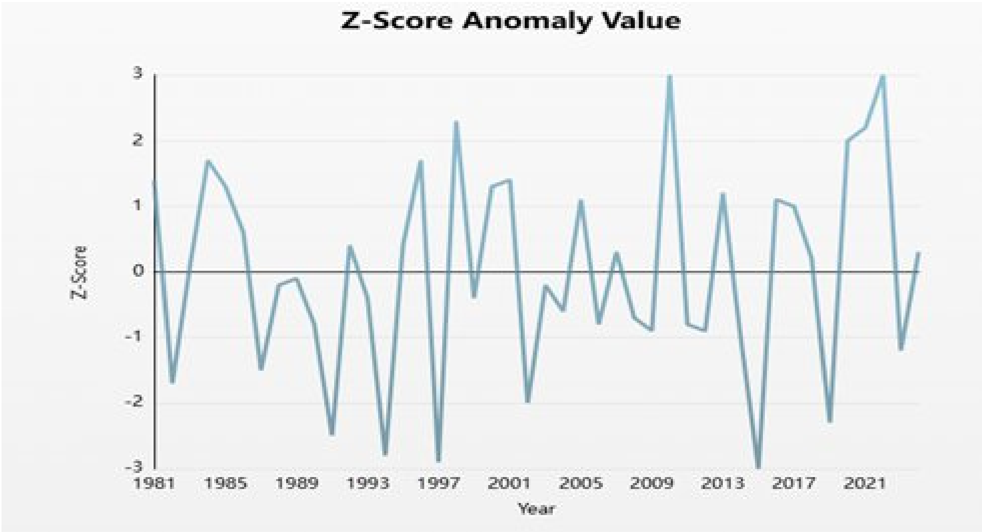

Figure 6 Graphical Display of Annual Anomaly Z Scores

The following is a summary of the Z-score anomaly analysis considering several variables:

a. High Variability: The graph shows sharp fluctuations in the blue line, not stagnant at 0. This indicates that Palembang frequently experiences rapid climate change during the dry season.

b. Very Wet Periods (Extremely above normal): There are several significant peaks, particularly in the 2010,2022 period, with the Z-score reaching its highest level (3 on the Y-axis). This condition reflects a much wetter than normal rainy season, even indicating extreme hydrometeorological events.

c. Very Dry Period (Much below normal/drought): Some phases show very low Z scores approaching -3 or even reaching the maximum, such as in 1994, 1997, and 2015. This period is likely related to a strong El Niño event, which generally triggers more severe drought conditions in southern Indonesia, including Palembang (there was even haze that year).

d. Long-Term Trend: Visually, there is no consistent linear upward or downward trend over the 35+ years of data. The emerging pattern is more cyclical, following the cycle of climate anomalies such as El Niño and La Niña, which cause irregular alternations between wet and dry years.

e. Current Conditions: at the end of the graph (last 3 years), the Z score appears to be approaching 0(zero), indicating conditions approaching normal seasons.

In the filtering and mapping process, the CHIRPS map function is used to ensure that the same procedures are applied consistently for each month from January to December. Through this filtering, all rainfall data from other years or months is ignored, so that only daily rainfall data for a specific month in 2024 is retained. The next step is to accumulate monthly rainfall. This step converts the daily data into a total rainfall map for each month. If necessary, a unit conversion process is performed, which is to multiply the result by a factor using.

Multiply factor to ensure that the measurement units are consistent (for example, from millimeters per day to total millimeters per month). Next, the algorithm summarizes all the information on the map into a single representative value that describes the average rainfall in the Palembang region. This stage condenses thousands of data pixels into a single number. The final reduced value is then stored as a Feature Collection in monthly Rainfall 2025. This result is an important summary that shows the comparison of rainfall between months—which months are wet, which are relatively dry, and which have the lowest rainfall, which can indicate the peak of the dry season.

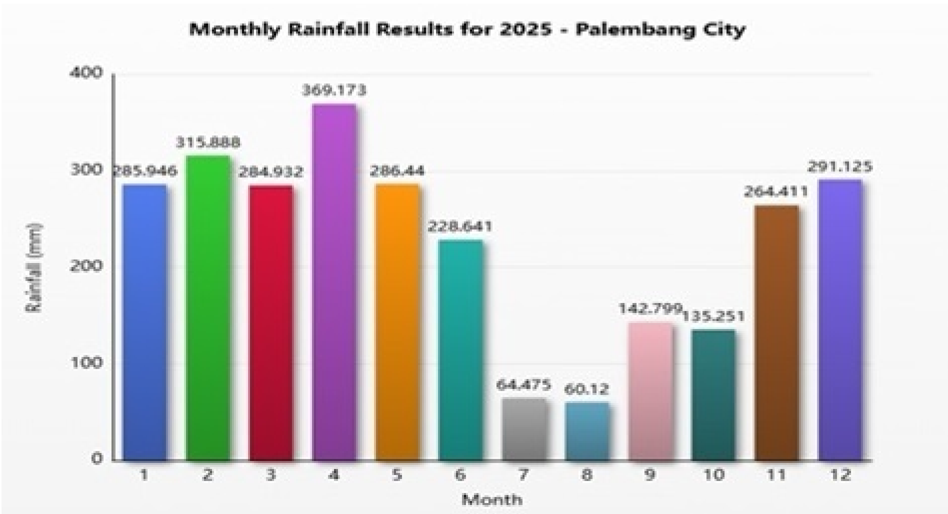

Figure 6 Graph Display of Monthly Rainfall Prediction Results for 2025

Based on the visual graph of monthly rainfall in 2025 or Figure 6, Palembang City experiences two significantly different seasons in a year. This can be proven by analyzing each bar of the monthly graph, which shows that there are:

1. High Rainfall Period (Rainy Season): Occurs at the beginning and end of the year, especially from January to May and December, with the highest rainfall peak occurring in April (around 360 mm). Rainfall increases again in November and December.
2. Low Rainfall Period (Dry Season): Occurs in the middle of the year, from June to October. The peak of the dry season or the driest months are predicted to occur in July and August, when rainfall is very low (around 60 mm).

Implementation and Test Results

This study presents source code and graphical visualizations to illustrate the rainfall assessment parameters that serve as key indicators in determining the research results. The research implementation is supported by data processed through the Google Earth Engine open-source platform, which provides relevant algorithms for conducting climate analysis and predictions in accordance with the context of this study. Based on the summary and algorithm test results, there are three main points from the implementation of this research:

1. Analysis of Dry Season Determination. The analysis was conducted based on rainfall fluctuations, identification of rainfall peaks, and determination of the lowest rainfall point as the main indicator in determining the dry season phase.
2. Analysis of rainfall anomalies is converted into standardized Z-scores. The calculation of anomaly Z-scores is influenced by several factors, such as high rainfall variability, periods of very high or very low rainfall, long-term trend patterns, and integrated climatological data updates.
3. Final Prediction Results. The output of the applied algorithm identifies periods of high rainfall (rainy season) and periods of low rainfall (dry season), which can be used as a basis for classifying climatic conditions in each period.

Conclusions

Based on the analysis results explained above, it can be concluded that the research method using the standardization method for anomaly Z-score assessment is able to predict rainfall in Palembang City effectively. This model has been running with the results of identifying the transition period from the rainy season to the dry season, namely from May to October, with the lowest rainfall occurring in August 2025. Furthermore, this model also determined the peak rainy season period from November to April, with the highest rainfall occurring in April 2025. The Z-Score Anomaly Assessment uses cumulative calculations for the climate period of approximately the last 30-40 years, from 1981 to 2024, which shows significant anomalies in historical climatology. For the rainfall anomaly value, it has been converted into a z-score value that has been desc`ribed using a formula so that the significance trend of the climate in 2024 is 0.34 according to the Standardized Precipitation Index (SPI) in the normal or mild condition category. Meanwhile, the 2025 rainfall prediction graph shows the final results of the analysis process, with the highest rainfall of 369.17 mm in April and the lowest rainfall of 60.12 mm in August. As a contribution, this study makes a significant contribution to the local hydrometeorology literature by demonstrating the effectiveness of historical climate anomaly assessment in improving the accuracy of region-specific weather predictions over a relatively long period of time. Practically, the results of this modeling can serve as a strategic tool for the

Palembang City Government and related sectors (such as natural resources and disaster management) in designing early warning systems and mitigating the impacts of extreme weather. Suggestions for Future Development To improve the accuracy and scope of future research, three key points are recommended: First, Integration of New Variables: Adding global climate parameters such as the El Niño-Southern Oscillation (ENSO) index or the Indian Ocean Dipole (IOD) to capture broader anomaly patterns. Second, Algorithm Optimization: Consider using advanced machine learning techniques or hybrid modeling to compare climate performance and rainfall patterns. Third, Real-Time Validation: Synchronizing prediction data with field observation stations in real time to validate model deviations against dynamic microclimate changes. Thus, all assessment elements in this study are complete and can be used as a scientific reference and policy basis for assessing the suitability of rainfall conditions.

References

Alejo, L., & Alejandro, A. (2021). Validating CHIRPS ability to estimate rainfall amount and detect rainfall occurrences in the Philippines. *Theoretical and Applied Climatology,* 145, 967 - 977. https://doi.org/10.1007/s00704-021-03685-y.

Alzian, N., Chenoli, S., Nor, M., Yik, D., & Samah, A. (2025). Spatial and temporal variability of extreme rainfall events over Peninsular Malaysia. *Hydrological Sciences Journal,* 70, 1365 - 1383. https://doi.org/10.1080/02626667.2025.2479106.

Amir, F., Sham, F., El-Shafie, A., Binti, W., Jaafar, W., Adarsh, S., Sherif, M., & Ahmed, A. (2025). Improving rainfall forecasting using deep learning data fusing model approach for observed and climate change data. *Scientific Reports*, 15. https://doi.org/10.1038/s41598-025-13567-2.

Andriyana, Y., Falah, A., Ruchjana, B., Sulaiman, A., Hermawan, E., Harjana, T., & Lim-Polestico, D. (2024). Spatial Durbin Model with Expansion Using Casetti's Approach: A Case Study for Rainfall Prediction in Java Island, Indonesia. *Mathematics*. https://doi.org/10.3390/math12152304.

Balogun, A., & Tella, A. (2022). Modelling and investigating the impacts of climatic variables on ozone concentration in Malaysia using correlation analysis with random forest, decision tree regression, linear regression, and support vector regression. *Chemosphere,* 134250. https://doi.org/10.1016/j.chemosphere.2022.134250.

Dhawan, P., Torre, D., Niazkar, M., Kaffas, K., Larcher, M., Righetti, M., & Menapace, A. (2024). A comprehensive comparison of bias correction methods in climate model simulations: Application on ERA5-Land across different temporal resolutions. *Heliyon,* 10. https://doi.org/10.1016/j.heliyon.2024.e40352.

Du, H., Tan, M., Zhang, F., Chun, K., Li, L., & Kabir, M. (2023). Evaluating the effectiveness of CHIRPS data for hydroclimatic studies. *Theoretical and Applied Climatology,* 155, 1519 - 1539. https://doi.org/10.1007/s00704-023-04721-9.

Durowoju, O., Obateru, R., Adelabu, S., & Olusola, A. (2025). Urban change detection: assessing biophysical drivers using machine learning and Google Earth Engine. *Environmental Monitoring and Assessment,* 197. https://doi.org/10.1007/s10661-025-13863-4.

Garajeh, M., Haji, F., Tohidfar, M., Sadeqi, A., Ahmadi, R., & Kariminejad, N. (2024). Spatiotemporal monitoring of climate change impacts on water resources using an integrated approach of remote sensing and Google Earth Engine. *Scientific Reports,* 14. https://doi.org/10.1038/s41598-024-56160-9.

Gwatida, T., Kusangaya, S., Gwenzi, J., Mushore, T., Shekede, M., & Viriri, N. (2023). Is climate really changing? Insights from analysis of 30-year daily CHIRPS and station rainfall data in Zimbabwe. *Scientific African*. https://doi.org/10.1016/j.sciaf.2023.e01581.

Habibie, M., Nurda, N., Sencaki, D., Putra, P., Prayogi, H., Agustan, A., Sutrisno, D., Bintoro, O., Yulianto, S., & Arifandri, R. (2024). Assessing Regional Precipitation Patterns Using Multiple Global Satellite-Based Datasets in the Upper Citarum Watershed, Indonesia. *Journal of the Indian Society of Remote Sensing*. 52. https://doi.org/10.1007/s12524-024-01952-9.

Levin, E., Beisekenov, N., Wilson, M., Sadenova, M., Nabaweesi, R., & Nguyen, L. (2023). Empowering Climate Resilience: Leveraging Cloud Computing and Big Data for Community Climate Change Impact Service (C3IS). *Remote. Sens*., 15, 5160. https://doi.org/10.3390/rs15215160.

Rahayu, R., Mathias, S., Reaney, S., Vesuviano, G., Suwarman, R., & Ramdhan, A. (2022). Impact of land cover, rainfall and topography on flood risk in West Java. *Natural Hazards*, 116, 1735-1758. https://doi.org/10.1007/s11069-022-05737-6.

Sharafi, S., & Ghaleni, M. (2021). Evaluation of multivariate linear regression for reference evapotranspiration modeling in different climates of Iran. *Theoretical and Applied Climatology*, 143, 1409 - 1423. https://doi.org/10.1007/s00704-020-03473-0.

Simanjuntak, N., Sudarisman, M., Darmawan, Y., & Saragih, I. (2024). Accuracy of CHIRPS rainfall data and its utilization in determining the onset of the wet and dry seasons in North Sumatra. *MAUSAM*. https://doi.org/10.54302/mausam.v75i3.6262.

Sun, D., Wu, J., Huang, H., Wang, R., Liang, F., & Hong, X. (2021). Prediction of Short-Time Rainfall Based on Deep Learning. *Mathematical Problems in Engineering*, 2021, 1-8. https://doi.org/10.1155/2021/6664413.